Title
Market-Share Analysis: A Core Technology for Learning About Markets and Competition

Authors
Cooper, Lee
Nakanishi, Masao

Publication Date
2023-12-14

Market-Share Analysis: A Core Technology for Learning About Markets and Competition

Lee G. Cooper
Anderson Graduate School of Management
UCLA, Los Angeles, U.S.A.
and
Masao Nakanishi
School of Business Administration
Kwansei Gakuin University, Nishinomiya-shi, Japan

Summary

The current state of market-share analysis is summarized according to the five-stage model described in Cooper and Nakanishi (1988). Consideration of what is needed to help managers learn about markets and competition leads to a discussion of CHAINs (Combined Human- and Artificial-Intelligence Networks)—open systems in which growth of the *knowledge base* is the primary concern.

1 Introduction

The salient characteristics of the contemporary marketing environment are that the data resources are vast and growing, and that expertise, while substantial, is disjoint and incomplete. The data resources are best represented by the enormous scanner databases reflecting a complete record of retail transactions at the store level (as well as the promotional environment in which these transactions occur) and reflecting the over-time purchases of members of huge consumer panels. The consumer panels are now providing records of television-viewing behavior—a micro record of advertising exposures which can be linked directly to purchases in the relevant categories.

The new challenge these data create concerns what it means to manage in an information-rich environment. What should managers do with the millions of new and relevant numbers which become available each week? The expertise available to confront this task is disjoint in that the methodological expertise for dealing with these vast data is being developed predominantly by marketing academics and the modeling staffs of the syndicated data sources such as A.C. Nielsen, Information Resources Inc., and SAMI/Burke, while the existing brand-management expertise and the knowledge of each product domain is held by the brand-management groups of various manufacturers, and knowledge of the retail environment is shared by brand managers and managers in the channels of distribution. The expertise is incomplete in that academics and practitioners are still very early on the experience curve. There is much left to learn.

But with marketing academics becoming intrigued by the challenges of these new data, and with marketing professionals turning toward technology to help them cope with an

NATO ASI Series, Vol. F 61
Knowledge, Data and Computer-Assisted Decisions
Edited by M. Schader and W. Gaul

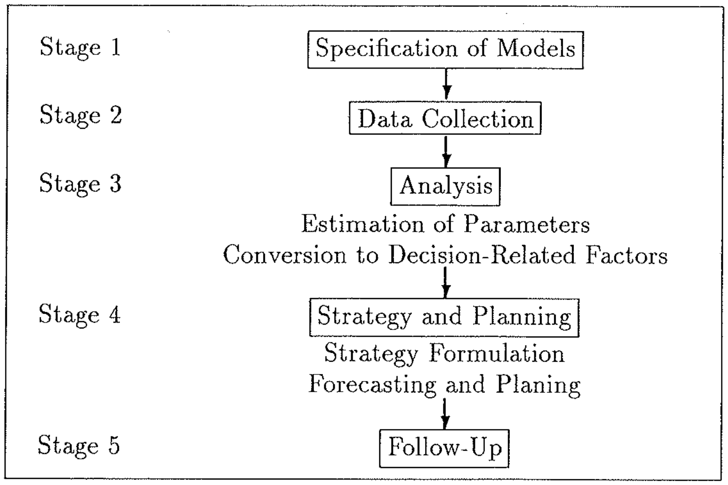

Figure 1: The Five Stages of Market-Share Analysis

information-rich environment, there has evolved a rare alignment of agendas between the academic and professional communities. Sensing the early, but obvious signs of this alignment, we decided to write *Market-Share Analysis: Evaluating Competitive Marketing Effectiveness.* This book started with a shared vision of the future role of technology in management (which some of our colleagues have called "The Starship Enterprise"), and how technology could aid managers trying to learn about the competitive environment. The goal of this chapter is to describe the process of learning we call *market-share analysis.* In section 2 the five-stage model for market-share analysis is described. Section 3 summarizes three new developments that help make market-share analysis a more practical and broadly applicable approach to learning about markets and competition. And, since the most wonderful aspect of our time is the speed at which technology overtakes our fantasies, we relate in Section 4 a vision of how future technology can be adapted to our tasks.

2 The Process of Market-Share Analysis

The three key characteristics are that market-share analysis is *competitive, descriptive* as well as predictive, and *profit-oriented. Competitive* implies that the effect of one's actions must be analyzed in conjunction with the market positions and actions of competitors. We must differentiate the forces which affect one's product/brand from the more general factors which affect the whole industry. To be *descriptive* as well as predictive indicates we are not satisfied with a forecast unless it tells us how our marketing actions and those of our competitors affect outcomes. Such diagnostic information is essential for brand planning. Being *profit-oriented* means that we must consider the costs and revenues associated with marketing actions, not just the market-share response. With these characteristics in mind, market-share analysis can be thought of as the five-stage process shown in Fig. 1.

The first stage involves specification of models. While this stage is indispensable since the choice of model determines the data requirements in the data-collection stage, a more fundamental purpose is being served here. Model specification requires management to come to a common understanding of the variables that affect performance in a competitive environment and how those variables relate to each other. This common understanding can be very helpful in getting organization members to interpret and value market outcomes from the same point of view. The perspective offered most dominantly in the book is that the set of measures should be as comprehensive as possible and that all the measured aspects interact to form the attractiveness of an offering in the marketplace. A second fundamental perspective is that while the raw level of marketing activities affects the total volume of sales for all brands in the category, it is the distinctiveness of marketing actions which counts in determining market shares.

The second stage involves data collection and review. While many organizations are well equipped to track information on their own activities, the fundamental *competitiveness* of market-share analysis urges organizations to measure on the competitors whatever they track for their own brands. The scanner databases have been the biggest boon in making available the kind of competitive information which is otherwise often too difficult to obtain.

The third stage involves both the estimation of model parameters and the conversion to decision-related factors. Regarding parameter estimation the book describes methods for calibrating MCI (Multiplicative Competitive-Interaction) Models and MNL (Multinominal Logic) Models. Simple-effects versions of these models reflect a world in which each brand can have its own level of loyal consumers, but all brands share a common sensitivity to changes in the levels of each marketing variable. The attraction function and the relation of attraction to market share are summarized as follows:

$$\mathcal{A}_i = \exp(\alpha_i + \epsilon_i) \prod_{k=1}^{K} f_k(X_{ki})^{\beta_k} \tag{1}$$

$$s_i = \mathcal{A}_i / \sum_{j=1}^{m} \mathcal{A}_j \tag{2}$$

where parameters α_i $(i = 1, 2, \ldots, m)$ are constant, brand-specific effects representing the marketing effectiveness of the respective brands, ϵ_i reflects specification error, X_{ki} are the marketing instruments $(k = 1, 2, \ldots, K)$ for brand i $(i, j = 1, 2, \ldots, m)$, $f_k(\cdot)$ is a positive, monotone function[1], and β_k is a parameter for the sensitivity of all brands to changes in variable k. Equation (2) shows how attraction translates into market share s_i for brand i.

The inclusion of the α's in attraction models, however, does not fully account for differential effectiveness among brands. The differential effectiveness may be specific to each marketing instrument, such as a brand which has a particularly effective pricing policy or an effective advertising campaign. The α_i's do not appear in the elasticity formulas for a particular marketing instrument, X_k (namely, $e_{s_i} = \beta_k(1 - s_i)$ for MCI models and $e_{s_i} = \beta_k X_{ki}(1 - s_i)$ for MNL models). The *marketing-effectiveness* parameters may reflect differences in the *brand franchise* or *brand loyalty*. Literally, they are the constant component of each brand's attraction, but they have nothing to do with elasticities. As a result, elasticity formulas for simple attraction models do not reflect differential effectiveness.

[1]If $f_k(\cdot)$ is the exponential transformation Equation (1) specifies a MNL Model. If $f_k(\cdot)$ is the identity transformation Equation (1) specifies an MCI Model. $f_k(\cdot)$ may also be used to reflect how the raw marketing instruments are transformed to reflect the distinctiveness of marketing activities—using *z-scores* in the MNL Model or *zeta-scores* in the MCI Model.

If we wish to reflect a world in which brands are differentially effective in implementing their marketing programs, this may be achieved in only one way, that is, by specifying parameters β_k's in such a manner that each brand has a special parameter, β_{ki}, for variable X_k. The attraction component of the differential-effect market share model is represented as follows:

$$\mathcal{A}_i = \exp(\alpha_i + \epsilon_i) \prod_{k=1}^{K} f_k(X_{ki})^{\beta_{ki}} \tag{3}$$

Cross-competitive-effects (asymmetric) versions of these models allow further that brands can be differentially sensitive to the actions of particular competitors.

$$\mathcal{A}_i = \exp(\alpha_i + \epsilon_i) \prod_{k=1}^{K} \prod_{j=1}^{m} f_k(X_{kj})^{\beta kij} \tag{4}$$

where β_{kij} is the parameter for the cross-competitive effect of variable X_{kj} on brand i.

Equation (4) is called an attraction model with differential cross-competitive effects or a *fully extended* attraction model to distinguish it from a differential-effect attraction model (3). The most important feature of the fully extended model is that the attraction for brand i is now a function not only of the firm's own actions (variables X_{ki}'s, $k = 1, 2, \ldots, K$), but also of all other brands' actions (variables X_{kj}'s, $k = 1, 2, \ldots, K; j = 1, 2, \ldots, m$). The β_{kij}'s for which i is different from j are the *cross-competitive effect* parameters. The β_{kij}'s for which j equals i (i.e., β_{kii}) are *direct-effect* parameters and are equivalent to the β_{ki}'s in the differential-effect model (3). This notation is cumbersome, but it is necessary to keep track of who is influencing whom. Note that the fully extended model has many more parameters (with $m \times m \times K$ β_{kij}'s and m α_i's) than the original attraction model (with $K + m$ parameters) and the differential-effect model (with $m \times K + m$ parameters).

When there are sufficient degrees of freedom to estimate all these cross-effect parameters, model calibration is straightforward[2]. But for the cases in which one expects many of the cross-effect parameters to be insignificant, a statistical expert system (SES) has been developed to estimate the parameters of these models. There are 15 steps which have been integrated into a SAS$^{(R)}$ program (called MACRO MCI) to perform the analytical tasks in estimating asymmetric market-share models.

1. Form the flat file containing variables [Sales plus Marketing Instruments] and observations [Brands $\times$ Stores $\times$ Weeks].

2. Choose the model form (MCI or MNL) and the transformations of variables (zeta-scores, exp(z-scores), or raw scores).

3. Form the differential-effects file containing the expanded set of variables [Sales + (Instruments + 1) $\times$ Brands] for the same observations.

4. Form the differential-effects covariance matrix and store.

5. Estimate the differential-effects model.

[2] We have known for a long time (Nakanishi and Cooper (1974)) that these nonlinear market-share models can be linearized by log centering (dividing each sides of the market-share equation by its geometric mean and then taking the log of each side).

6. Find the brand intercept nearest zero and delete.

7. Re-estimate the differential-effects model.

8. Compute the residuals and sort by brand.

9. Cross correlate each brand's residuals with the marketing instruments of every competitor.

10. Tally the significant cross correlations.

11. Form the differential cross-effect variables.

12. Compute and store complete covariances (differential effects and cross-competitive effects).

13. Simultaneously re-estimate the parameters for all the effects in the calibration data.

14. Estimate WLS or GLS weights and re-estimate parameters.

15. Cross validate on fresh data.

This macro program makes it practical to estimate the parameters of large-scale market-share models. The first step in converting model results to decision-related factors is the computation of elasticities. But in using more and more realistic market-share models we find that elasticities change with market conditions. Constant-elasticity models reflect far too simplistic a view of markets and competition. To represent the elasticities which characterize market behavior we discuss a second step involving both competitive maps and models which can locate ideal points or vectors in those maps. We have a brand $\times$ brand array of cross elasticities for each time period and/or store. The systematic structures underlying this three-mode array can be revealed using a special case of three-mode factor analysis (Tucker (1969), Cooper (1988)). There are two kinds of graphic outputs. The first summarizes the competitive structure over time and/or stores. Given what is known about the competitive activity at each place and time, this display helps identify what produces the major shifts in competitive structure. We can then create the second graphic display—¡a brand map—corresponding to each of these major shifts in competitive structure. The brand-to-brand competition represented in brand maps recognizes that two basic patterns need to be reflected. First there is a pattern of how each brand exerts influence over all the brands in the market. Similar positions in this pattern indicates that two brands exert similar kinds of influence over all other brands. And second there is the pattern of how brands are influenced by marketplace forces. Similar positions in this pattern indicate that two brands are influenced by the same basic forces in the marketplace. Brands can differ in their clout (i.e. their ability to exert influence) and they may differ in the vulnerability (i.e. their ability to be influenced by other brands or their receptivity to their own marketing actions). The brand map represents these two sides of the influencing process by a joint space. Each brand appears twice—once to reflect its clout and once to reflect its vulnerability. The length of the clout vector reflects the overall clout of a brand, just as the length of a vulnerability vector reflects the overall vulnerability of a brand. The angle between brand A's clout vector and brand B's vulnerability vector reflects the cross-competitive pressure A exerts on B.

The ability to imbed ideal points or preference vectors into a competitive map is merely an additional device to aid in interpretation of the spatial relations. The decision-support software CASPER was designed to help with Stage 4: Strategy and Planning. CASPER was designed with three principles in mind. First, managers must be able to learn from history. Thus a year worth of historical data, covering nine coffee brands and three grocery chains, was incorporated into CASPER along with the graphing utilities to be able to summarize each brand's performance over time or the performance of all competitors in a single time period. Second, managers must be able to simulate the consequences of any competitive scenario in terms of sales, costs, and revenues for all competitors in the marketplace. Thus the asymmetric market-share model and category-volume model developed in Chapter 5 of the book were incorporated into CASPER's simulator, along with the basics of financial analysis—allowing managers readily to assess the impact of a plan on costs and revenues. The simulator is an *inference engine* in the planning system. It describes how each of the marketing actions of each brand translates into sales. We do not understand how data are useful for planning without an *inference engine* of this sort. And third, managers must be able to test out a proposed plan in a dynamic, competitive environment. And thus a dynamic simulator was created in the form of a promotion-analysis game with three game periods of nine weeks each. Brand managers and store managers can compete against each other and against the results obtained by the real brands and stores in the corresponding time periods.

Stage 5 involves follow up. It is critically important that the analyst reviews the performance of a firm's product/brand after the marketing plans are put into effect. Discrepancies between forecasts and performance might be due to errors in forecasting industry sales, errors in forecasting market shares or that marketing activities were not carried out as planned by the firms or competitors' activities were not as anticipated. The sources of errors must be isolated so that the proper remedial actions are undertaken for the next planning cycle.

3 New Developments

There are three new areas explored in the book that make market-share analysis more broadly applicable. These deal with time-series issues, issues in collinearity, and estimation of the fully extended (cross-competitive effects) models.

3.1 Time-Series Issues

One of the most fundamental properties of attraction models has been that they produce logically consistent estimates of market shares (i.e. market shares are non-negative and sum to one over all competitors in a time period and/or region). It has been believed that this very desirable property was lost if lagged dependent variables were incorporated into the attraction specification. The book demonstrates (Sections 3.9 and 3.10) that lagged dependent and/or independent variables can be incorporated into MCI or MNL models without losing the logical-consistency property as long as the specification is done with log-centered variables.

3.2 Issues in Collinearity

The primary objection to log centering as a way of linearizing the market-share equation was that in differential-effects models or cross-competitive-effects models log centering somehow induced high collinearity even if the original variables were only modestly correlated (Bultez and Naert (1975), Naert and Weverbergh (1981)). Section 5.6 demonstrates three important results. First, the high collinearity observed in differential-effects models or cross-competitive-effects models is not due to log centering. It is present in linear, multiplicative and attraction specifications of market-share models if the explanatory variables are expressed in either raw or share form. Second, using distinctiveness coefficients such as either exp(z-scores) or zeta-scores effectively controls the collinearity in these equations. Third, when viewed as a numerical-analysis problem, collinearity becomes serious when the cross-products matrix can not be inverted. But the special structure of the cross-products matrix from a differential-effects attraction model makes it robust against high correlations induced by the model's structure. It should be invertible when the original variables themselves are not extremely correlated.

3.3 Estimation of the Fully Extended Model

The fully extended model has a parameter for every cross-competitive effect of each brand's full complement of marketing instruments on each other competitor. Thus with K marketing instruments on each of m brands the model would estimate a total of $(m + K \times m^2)$ parameters. When sufficient degrees of freedom are available to estimate this many parameters a very simple multivariate regression model can be used. Section 5.8 points out that OLS procedures produce the best linear-unbiased estimates (BLUE) of the parameters. It is not necessary to resort to GLS procedures to obtain minimum-variance estimates of this model.

4 A Look to the Future

Chapter 8 in the book briefly delineates a research agenda dealing with estimation problems, integration of panel data and store-level data, market-basket models, and issues in decision support.

The agenda concerning estimation problems involves dealing with missing data, developing constrained parameter estimates, and determining the long-run effects of marketing actions. Missing data are a concern in estimation of the category-volume model and the fully extended attraction model. We want to use all the data that are available, but want the missing elements in each observation have as little influence on the parameter estimates as possible. Cooper, de Leeuw and Sogomonian (1989) have recently developed an algorithm to impute the missing values in this way. Regarding constrained parameters we note that managers (dealing with FPBGs) expect all price parameters to have a negative sign and all promotion parameters to have a positive sign. This can be achieved through constrained parameter estimation. But these procedures should be thoroughly investigated before a well-reasoned decision on parameter-estimation methods is made. Regarding long-run effects Hanssens (1987) shows that no permanent effects of marketing action could be found in 106 tests on scanner data relating to instant coffee. But further study is needed to detect if differences in the brand-specific intercepts could be related to differences in national advertising or other variables which are typically not included in scanner data sets.

The book relies predominantly on store-level data for market-share analysis, while many market modelers have followed the path of Guadagni and Little (1983) in developing models based on scanner panels. The integration of these data sources is now a reality, but the methods to use both data in analyzing market response require much further development. Moore and Wine (1987) report the only published research in this important domain.

Many of the issues of interest to retailers center on purchases across product categories (e.g. shelf-space allocation). The ultimate extension of the ideas in the book will be to create a system of hierarchically organized category-volume and market-share models which collectively reflect the competitive interplay among all the items in a market basket.

The issues in decision support focus on needed developments in game theory and extensions of expert systems. Generalizing game theory to reflect all the competitive influences described in the book will be a difficult task, but realistic scenarios are needed if policy implications usually stemming from game-theoretic analyses are to be useful for management in information-rich environments. Regarding traditional expert systems it is important to note that they are not learning systems. Yet learning is what is so clearly called for at this stage of development. The following section deals with the creation of learning systems.

4.1 From CASPER to CHAINs

A **CHAIN** is a Combined **H**uman- and **A**rtificial-**I**ntelligence **N**etwork. Explicitly considering the role of human intelligence in a management system encourages us to take a broader, open-systems view of the process. Open systems have semi-permeable boundaries with the environment. Such systems actively regulate the flow of information and other resources across their boundaries in a purposeful effort to achieve system goals. Opens systems can learn from their interaction with the environment. A traditional expert system, on the other hand, is a closed system once the knowledge engineering has taken place. The human role is merely to provide input to the closed expert system, and to receive the answer. There is no learning on the part of the expert system.

Consider a manager/management scientist sitting at a microcomputer with CASPER as the two central links in a CHAIN. What more is needed to facilitate learning? Having helped a few generations of students through this learning process, we see the need for several developments. Fig. 2 summarizes the key functions and relations. As stated earlier, a manager must be able to learn from history. The raw data in a *fact base* are of very limited use until they are visualized using graphics generators and/or report generators. The increasing importance of graphics in summarizing vast amounts of information and driving the interactions between humans and computers is why we refer to visualization stations rather than workstations. So we need to plan for graphic information as well as numeric and textual information in a *fact base*. CASPER's standard graphic libraries begin this process by summarizing within-brand performance over time and across-brand performance within a time period. CASPER currently summarizes history in spreadsheets reflecting store-level sales. This will have to evolve so that CASPER links to CD-ROM databases with both store-level data and scanner-panel data included. Textual databases

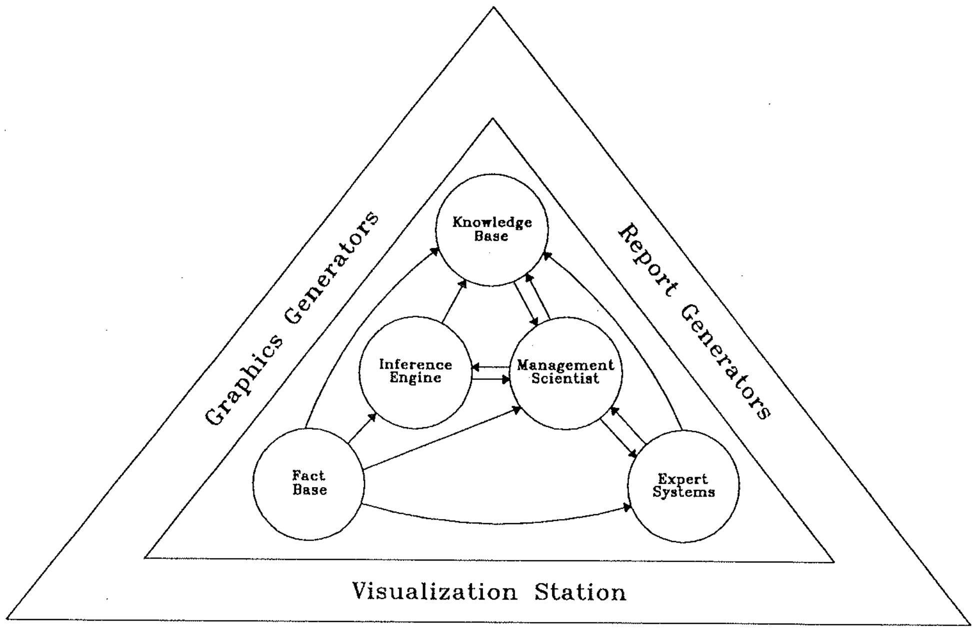

Figure 2: An Open-Systems Model for Learning About Markets and Competition

will also have to be integrated.

The *knowledge base* at any point in time is considered to be open and partial. The emphasis in the open system is on growth in the knowledge base. While facts themselves are best considered as separate from the *knowledge base*, the linkages between entities in the *fact base* are part of the *knowledge base*. The process of inquiry of MBA students and managers typically begins by reviewing the past performances of brands (both over time and across different retail outlets), looking for patterns. Their inquiry could be more systematic if they could create hypertext linkages to written notes concerning store policies and interactions between brands, hypermedia linkages to all graphs relating to particular issues or linkages between notes and graphs. Searches could be made for all notes referring to a brand or a topic or to all graphs mentioned in some set of notes. A permanent record of the preliminary inquiry process—reflecting both the insights and the blind alleys, could help others to move more rapidly along the experience curve.

The most basic function of CASPER is as an *inference engine* allowing a manager/management scientist to translate hypothetical market conditions into forecasts of market response. Imbedding even a complex market-response model in a spreadsheet is a trivial task, but making it useful as an *inference engine* requires far greater functionality. A manager needs to be able to visualize the results of simulations. Numeric and graphic databases will have to be created from the results of CASPER simulations. Hypertext or hypermedia linkages again have a very important role in organizing the *knowledge base* to be useful for inquiry. Also the manager/management scientist must be able to evaluate the *model base* (a component in the *knowledge base*) periodically to assess if the inference engine requires recalibration. This opportunity arises each time the *fact base* is refreshed with new market data. CASPER currently has functions which will run a new mass of data through the *inference engine* to help assess if the model is still a good predictor.

A naive approach to the use of the *inference engine* is to manipulate all the major variables for all the major brands. Testing the influence of newspaper features, in-store displays, store coupons at just five price levels for the three major brands in the coffee-market example in CASPER would require 64,000 iterations. It is obvious that thoughtful consideration is needed in selecting the market scenarios to run through the *inference engine*. Competitive maps should be linked into the *knowledge base* so that they have a more integral role in choosing which scenarios to simulate. But to use these complex maps more readily we need to develop real-time animation. Motion and choice of orientation are very useful techniques for aiding the visual understanding of these high-dimensional information spaces. To be able to rotate these maps and look at the competitive patterns from each brand's point of view would be very helpful.

We also need the ability to bring a auxiliary information (e.g. prices and promotions) from the *fact base* into the competitive-structure graphs to help managers interpret what causes shifts in the structure of the market. The competitive-structure graph is analogous to the *person space* in a multivariate individual-differences analysis (here the individuals are stores or store-weeks). After the millions of machine cycles needed to create such maps, the interpretation is still dependent on an analyst detecting a pattern when simple (often demographic) variables are used to label the points in the space. Given this dependency, we need less cumbersome procedures for using auxiliary information to label points in 3-dimensional space, and some artificial-intelligence algorithms to keep these labels from colliding as these spaces are rotated.

Expert systems have roles both in summarizing existing knowledge (i.e. the *received view* of knowledge in a domain) and in shaping the learning process. Instead of leading a manager/management scientist through a series of descriptive questions about the promotional environment in the formulation of an *expert* promotional plan, the systems could suggest the most informative simulations to run or the graphic summaries which might be most relevant to review Artificial-intelligence algorithms for exception reporting could be used to detect unusual patterns in the *fact base* or in the accumulating results of simulations. Artificial-intelligence algorithms have begun to be used in marketing to help investigators learn about the choice processes of individuals in scanner panels (Currim, Meyer and Le, (1988)). Similar *rule-learning algorithms* (cf. Michalski, (1983)) can be used to *learn* about aggregate market-response. These kinds of applications are worthwhile extensions of current uses. What is more problematic and challenging is the need for ways for the manager/management scientist to interact with the *rule base*—adding rules and reclassifying rules—without, on the one hand, compromising the integrity of the *expert system*, or, on the other hand, requiring managers to become knowledge engineers. Classification of rules into either *received view* or *evolving view* could allow the management scientist to evaluate a *rule base* in a manner similar to the evaluation of a *model base*. The important step is in the opening up of traditionally closed *expert systems*, and allowing of them to grow as knowledge expands.

So the *knowledge base* contains the hypertext or hypermedia linkages among entities in the *fact base* and the results of simulations, as well as the *model base* and the *rule base*. This makes a CHAIN seem like a hypermedia application, which it almost is. But current industry thinking about hypermedia is missing the crucial understanding of the human's (user's) role in building the hypermedia application.

The basic components of hypermedia systems are typically represented to include a video monitor, video-disk player, microcomputer and screen, CD-ROM drives and multimedia software. But this choice stems from a conceptualization of manufacturers as providers of all knowledge and users as recipients of knowledge. A CHAIN recognizes that the human subsystem is an active developer of knowledge which needs to be passed on. Thus CD-ROM should be replaced by or augmented with WORM (write once read many) drives or erasable optical disks. The emphasis is not on erasability, rather it is on writability or creatability. The quality of the creation should be at least as high as that of the received knowledge. Similarly, the video-disk player should be replaced by or augmented with hardware and software related to digital video-tape (DVT) and digital audio-tape (DAT) technologies. Stored knowledge, both methodological and managerial are both needed, but these are not the only ingredients. There must be a way for knowledge to grow and for that growth of knowledge to accumulate—becoming as integral to the system as the *received knowledge.*

There are serious barriers to the development of hypermedia applications. A recent survey of academics conducted by a field-study team at UCLA cited in order of importance: the time required to develop multimedia applications, technical support costs, data acquisition costs, lack of expertise regarding multimedia, lack of preconstructed multimedia databases in a particular subject area, and lack of financial resources. Academics do not in general believe that software developers can create multimedia databases for their specialities. Underlying this is, we believe, a realization that high-tech manufacturers are oriented to providing finished solutions which only require users. Whereas the concept of a CHAIN is that no part of a network should be so encapsulated that a multi-way linkage cannot be established of equivalent quality.

It is the multi-way linkages potentially going throughout the network which makes a CHAIN overcome the old saw that a chain is only as strong as its weakest link. In this sense a CHAIN is more like chain mail, than it is like the single-linkage versions.

References

BULTEZ, A.V., and NAERT, P.A. (1975), Consistent Sum-Constrained Models, *Journal of the American Statistical Association, 70, 351*, 529–535.

COOPER, L.G. (1988), Competitive Maps: The Structure Underlying Asymmetric Cross Elasticities, *Management Science, 34, 6*, 707–723.

COOPER, L.G., DE LEEUW, J., and SOGOMONIAN, A.G. (1989), An Imputation Method for Dealing with Missing Data in Regression, *UCLA Statistics Series 38.*

COOPER, L.G., and NAKANISHI, M. (1988), *Market-Share Analysis: Evaluating Competitive Marketing Effectiveness*, Kluwer Academic Publishers, Boston.

CURRIM, I.S., MEYER, R.J., and LE, N.T. (1988), Disaggregate Tree-Structured Modeling of Consumer Choice Data, *Journal of Marketing Research, 25*, 253–265.

GUADAGNI, P.M., and LITTLE, J.D.C. (1983), A Logit Model of Brand Choice Calibrated on Scanner Data, *Marketing Science, 2, 3*, 203–238.

HANSSENS, D.M. (1987), Marketing and the Long Run, *Center for Marketing Studies Working Paper 164*, Anderson Graduate School of Management, UCLA.

MICHALSKI, R.S. (1983), A Theory and Methodology of Inductive Learning, in: *Machine Learning: An Artificial Intelligence Approach*, eds. R.S. Michalski, J.G. Carbonell and T.M. Mitchell, Tioga Publishing, Palo Alto, CA, 83–134.

MOORE, W.L., and WINER, R.S. (1987), A Panel-Data Based Method for Merging Joint Space and Market Response Function Estimation, *Marketing Science, 6, 1*, 25–42.

NAERT, P.A., and WEVERBERGH, M. (1981), On the Prediction Power of Market Share Attraction Models, *Journal of Marketing Research, 18*, 146–153.

NAKANISHI, M., and COOPER, L.G. (1974), Parameter Estimation for a Multiplicative Competitive Interaction Model—Least Squares Approach, *Journal of Marketing Research, 11*, 303–311.

TUCKER, L.R. (1969), *Some Relations Between Multi-Mode Factor Analysis and Linear Models for Individual Differences in Choice, Judgmental and Performance Data*, Paper presented to the Psychometric Society Symposium, Multi-Mode Factor Analysis and Models for Individual Differences in Psychological Phenomena, April 18.

Knowledge, Data and Computer-Assisted Decisions

Edited by

Martin Schader

Institut für Informatik
Universität der Bundeswehr Hamburg
D-2000 Hamburg 70, FRG

Wolfgang Gaul

Institut für Entscheidungstheorie
und Unternehmensforschung
Universität Karlsruhe (TH)
D-7500 Karlsruhe, FRG

Springer-Verlag Berlin Heidelberg New York
London Paris Tokyo Hong Kong Barcelona
Published in cooperation with NATO Scientific Affairs Division

Proceedings of the NATO Advanced Research Workshop on Data, Expert Knowledge and Decisions, held in Hamburg, FRG, September 3–5, 1989.

ISBN 3-540-52712-5 Springer-Verlag Berlin Heidelberg New York
ISBN 0-387-52712-5 Springer-Verlag New York Berlin Heidelberg

Printed in Germany

Printing: Druckhaus Beltz, Hemsbach; Binding: J. Schäffer GmbH & Co. KG, Grünstadt
2145/3140-543210 – Printed on acid-free-paper

Contents